

Does task activation in task switching influence inhibition or episodic interference?

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Author Note

All raw data, code for the experimental program, as well as a reproducible version of this manuscript which includes the analysis code, can be downloaded from <https://osf.io/hdtqu/>. The Stage-1 accepted protocol can be downloaded from <https://osf.io/upvkh/>. I am grateful to Thinh Do and Harrison Smith for assistance with data collection. I am grateful to James Schmidt, Miriam Gade, and an anonymous reviewer for constructive comments on previous drafts of this paper. This study was supported by the Experimental Psychology Society (<http://www.eps.ac.uk/>).

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Abstract

N-2 repetition costs in task switching refer to slower responses to ABA sequences compared to CBA sequences, reflecting the persisting inhibition of task A across the ABA sequence. The magnitude of inhibition is thought to be sensitive to activation levels of interfering tasks. This is supported by larger n-2 repetition costs when the response-cue interval (RCI) is reduced: At short RCIs, a just-performed task is highly active when a new task is required, triggering more inhibition. However, recent work has shown that much of the n-2 repetition cost measures episodic interference, rather than inhibition. The current study addressed whether RCI manipulations influence inhibition or episodic interference. N-2 repetition costs were considerably reduced when episodic interference was controlled. Increasing the RCI led to equivalent reductions in the n-2 repetition cost for inhibition and episodic components of the cost, but for the former the cost was entirely absent at longer RCIs. .

Keywords: Task switching; cognitive control; inhibition; episodic retrieval

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Does task activation in task switching influence inhibition or episodic interference?

Cognitive inhibition can be defined as “...the stopping or overriding of a mental process, in whole or in part, with or without intention” (Gorfein & Brown, 2007). In models of cognitive control, inhibition compliments activation processes by resolving interference between competing representations once activated (Norman & Shallice, 1986; Sexton & Cooper, 2017). A balance between activation of task-relevant representations and inhibition of task-irrelevant representations seems to provide an elegant solution to the so-called *stability–flexibility dilemma* (Goschke, 2000) that the cognitive system faces: In order to act in a goal-directed manner, the system must be able to select task-relevant representations, and maintain them in a *stable* manner so that task-irrelevant intrusions do not occur; at the same time, these representations must be *flexible* so that they can be removed at a moment’s notice when goals change. Inhibition can aid stability, by ensuring task-irrelevant representations are inhibited if they interfere with the activation of task-relevant representations; inhibition also aids flexibility, by inhibiting task representations when they are no longer required.

The stability–flexibility dilemma has typically been studied using the task switching paradigm (Grange & Houghton, 2014; Kiesel et al., 2010; Vandierendonck, Liefoghe, & Verbruggen, 2010). In this paradigm, participants are required to rapidly switch between simple tasks on multivalent stimuli. For example, participants might be presented with a circle appearing in one of the four corners of a square grid, and be asked to mentally move the stimulus according to one of three spatial-transformation rules (“horizontal”, “vertical”, “diagonal”), and make a spatially-congruent response as to where the stimulus would move to according to the rule (see Figure 1).

Inhibition is thought to aid successful task switching by inhibiting a recently-performed task when it is no longer required (but see Altmann & Gray, 2008 for a comprehensive model of task switching that does not require inhibition). Evidence for such an inhibitory mechanism comes from requiring participants to switch between three tasks (arbitrarily

labelled A, B, & C). Such a scenario reliably produces *n-2 task repetition costs*: slower response times (and sometimes poorer accuracy) to ABA sequences than to CBA task sequences (Koch, Gade, Schuch, & Philipp, 2010; Mayr & Keele, 2000), which is generally accepted to reflect the persisting inhibition of task A across the ABA sequence which slows down its reactivation on the final trial of the triplet. Inhibition has been shown to act upon many levels of task representations, including cue/preparation-related aspects (Gade & Koch, 2014; Grange & Houghton, 2010; Houghton, Pritchard, & Grange, 2009; Scheil & Kleinsorge, 2014), stimulus-related aspects (Sdoia & Ferlazzo, 2008), and response-related aspects (Philipp, Jolicoeur, Falkenstein, & Koch, 2007; Schuch & Koch, 2003).

Linking Inhibition to Activation

The *n-2* task repetition cost appears sensitive to the degree of activation of the competing task representations, suggesting that the amount of inhibition deployed is relative to the amount of interference experienced by the system. Evidence for a link between activation and subsequent inhibition comes from manipulating the response-cue interval (RCI), the time between the response to one task and the onset of the cue for the next task. It is a consistent finding that estimates of the *n-2* task repetition cost are increased with shorter RCIs (Gade & Koch, 2005; Grange & Houghton, 2009; Mayr & Keele, 2000). At short RCIs, the just-performed task is still in a highly-active state; thus, when a new task becomes activated, the high activation of the previous task generates interference, which needs to be resolved by inhibiting the previous task (leading to large *n-2* task repetition costs). At short RCIs, however, the just-executed task's activation has had more time to passively decay (e.g., Altmann & Gray, 2008; but see Horoufchin, Philipp, & Koch, 2011), so activation of the new task generates less interference, which requires less inhibition of the previous task (leading to small *n-2* task repetition costs; Gade & Koch, 2005).

This link between activation and inhibition in task switching was made explicit in a recent computational model of task switching, whereby Sexton and Cooper (2017) extended

the connectionist model of Gilbert and Shallice (2000) to account for $n-2$ task repetition costs. In the model, stimuli are represented as a pattern of activation across input units, and activation propagates through the network to three sets of response nodes, one for each of the three tasks. The activation of the response nodes are biased toward the relevant task via “task demand” units, which provide top-down activation of task-relevant response nodes, and inhibition of task-irrelevant response nodes. Activation of task demand units carry over into the next trial, such that when a task switches, activation of a new task demand unit will face interference from a still-active—but task-irrelevant—task demand unit. A

conflict-monitoring layer (e.g., Botvinick, Braver, Barch, Carter, & Cohen, 2001) in the model monitors the degree of interference between active task demand units; the degree of interference registered is then translated proportionally into an inhibitory signal which feeds back to the task demand units with the net effect that task-irrelevant demand units become inhibited. This model was able to reproduce the increase in $n-2$ task repetition costs with shorter RCIs as more interference is registered by the conflict monitoring units because more activation of the previous trial’s task demand unit carries forward.

Episodic Retrieval Account of the $N-2$ Task Repetition Cost

The evidence discussed thus far supports an active inhibitory mechanism—as measured by the $n-2$ task repetition cost—that deploys proportionally to the degree of interference experienced, which is relative to the activation levels of task-irrelevant representations. However, Grange, Kowalczyk, and O’Loughlin (2017)—extending the work of Mayr (2002)—have provided evidence that much of the $n-2$ task repetition cost can be explained by a non-inhibitory process: namely, episodic interference. This account suggests that elements of a performed task—such as the cue, target characteristics, and the response selected—become bound into a single representation and stored in episodic memory (e.g., Hommel, 1998, 2004; Logan, 1988). When this task is cued again, the most recent trace of this task is automatically retrieved from episodic memory (Logan, 1988, 2002). If the current

trial’s parameters differ to the retrieved episodic trace (e.g., a different response is required because the presented target is different), a mismatch cost occurs relative to if the retrieved episodic trace matches the current trial’s parameters (which will prime response selection). By this account, the $n-2$ repetition cost can be explained by a mismatch cost, because trial parameters typically differ across both instances of task A in an ABA sequence.

The contribution of episodic interference to the $n-2$ task repetition cost can be examined using the paradigm introduced by Mayr (2002), a variation of which is presented in Figure 1. Trial parameters can either match or mismatch across an ABA sequence: For example, if the target is in the same location for Task A across an ABA sequence, the same response will also be required (i.e., an $n-2$ response repetition); episodic retrieval would thus prime response selection, leading to fast response times (and a reduced $n-2$ task repetition cost). In contrast, an $n-2$ response switch would lead to a mismatch during episodic retrieval (because a different response is required on the current trial to that at $n-2$, which is retrieved from episodic memory), leading to slower response times (and a larger $n-2$ task repetition cost).

Across three experiments, Grange et al. (2017) consistently found larger $n-2$ task repetition costs for $n-2$ response switches (episodic mismatches) than $n-2$ response repetitions (episodic matches), although some evidence remained for a “residual” $n-2$ task repetition cost for episodic matches. The increased $n-2$ task repetition cost for $n-2$ response switches suggests a large contribution of episodic interference to measures of inhibition in task switching.

Given this, it raises the question whether experimental manipulations shown to modulate the $n-2$ task repetition cost are actually influencing episodic interference rather than inhibition. This possibility was demonstrated by Grange et al. (2017) in Experiment 2, where they examined the effect of cue–task complexity on the $n-2$ task repetition cost in the paradigm that controls for episodic interference. Previous work (Gade & Koch, 2014; Grange & Houghton, 2010; Houghton et al., 2009) has shown that complex cue–task pairings (e.g.,

using abstract shapes as cues) increases the $n-2$ task repetition cost relative to simple cue-task pairings (e.g., words that describe the task, such as “Horizontal”). This finding has typically been explained by complex cue-task pairings generating more interference in working memory during switching, which requires more inhibition. However, when Grange et al. (2017) examined this issue using the paradigm controlling for episodic interference, complex cue-task pairings only increased the $n-2$ task repetition cost for $n-2$ response switches (i.e., episodic mismatches); no clear effect of cue-task pairings was observed for the residual $n-2$ task repetition cost (i.e., episodic matches). This data suggested that—contrary to previous reports—cue-task complexity influences episodic interference, not inhibition.

The Current Study

The purpose of the current study was to re-examine the effect of RCI on the $n-2$ task repetition cost whilst controlling for episodic interference. This will establish whether the RCI manipulation is influencing task inhibition (Gade & Koch, 2005; Sexton & Cooper, 2017) or whether it actually influences episodic interference. This is an important question given the proposed theoretical link between activation and inhibition in models of task switching (Sexton & Cooper, 2017). Thus, the current work can directly address a key theoretical assumption in models of task switching.

The study utilises the paradigm of Mayr (2002) and Grange et al. (2017), but additionally manipulated the RCI between short (50ms) and long (1,000ms) values in separate blocks. The choice of absolute values for the RCIs in the current study was somewhat arbitrary. In the three studies examining the effect of RCI on the $n-2$ task repetition cost, there is no consistency in absolute values used: Mayr (2002) used values of 150ms and 650ms; Gade and Koch (2005) used values of 100ms and 1400ms; and Grange and Houghton (2009) used values of 100ms and 900ms. In Grange et al. (2017), which showed strong effects of episodic retrieval on the $n-2$ task repetition cost, we used a fixed RCI of 50ms. Using values of 50ms and 1000ms are thus in line with previous (albeit arbitrary)

choices.

There were two reasons for deciding to manipulate RCI blockwise. First, two previous studies reporting reduced $n-2$ task repetition costs with longer RCIs manipulated RCI in a block-wise manner (Grange & Houghton, 2009, Mayr (2002)). Second, trial-wise variation of the RCI has been shown to introduce effects on performance attributable to temporal distinctiveness of episodic memory traces (Grange & Cross, 2015; Horoufchin et al., 2011). Whilst of potential interest to the current study’s aims (i.e., assessing episodic retrieval effects), it is important to note that manipulating RCI block-wise ensures that temporal distinctiveness is equated between different RCI conditions (Grange & Cross, 2015); as previously stated, there is good evidence that the reduction of the $n-2$ task repetition cost with increasing RCI has been found in conditions of block-wise manipulation of RCI (Grange & Houghton, 2009; Mayr, 2002), and therefore temporal distinctiveness cannot be the main explanation for this observation. As such, I wanted to remove its contribution to the data, and therefore decided on a block-wise manipulation of RCI.

Four hypothetical outcomes on the $n-2$ task repetition cost are depicted in Figure 2. In Figure 2A, RCI has no effect on the $n-2$ task repetition cost for both $n-2$ response repetitions and switches. Despite the RCI effect appearing well-replicated (e.g., Gade & Koch, 2005; Grange & Houghton, 2009), this remains a possibility. Figure 2B depicts a scenario where RCI has an equal effect on the $n-2$ task repetition cost for response repetitions and switches. This outcome would suggest that RCI influences both inhibition and episodic interference. Figure 2C represents an outcome where the RCI manipulation only influences the $n-2$ task repetition cost for response switches; this would suggest that RCI has no effect on inhibition, but influences episodic interference. Figure 2D represents an outcome where RCI only influences the $n-2$ task repetition cost for response repetitions; as this residual cost controls for episodic interference, this outcome would suggest that the RCI does influence inhibition, and not episodic interference. A final possibility (not shown) is that the RCI affects the $n-2$ repetition cost for *both* response repetitions and switches, but the effect is larger for one than

the other, suggestive of a stronger effect of RCI for one level of response repetition.

Given the many outcomes that are possible with this manipulation, the registration of the experimental design and analysis strategy becomes more important so that researcher degrees of freedom (Simmons, Nelson, & Simonsohn, 2011) do not contribute to the final result.

Method

Participants & Stopping Rule

Participants were recruited from the School of Psychology at Keele University in return for partial course credit or cash payment (£10).

The stopping rule utilised sequential Bayes factors (Schönbrodt, Wagenmakers, Zehetleitner, & Perugini, 2017), using the methods for Bayesian analysis of factorial designs as outlined by J. N. Rouder, Morey, Verhagen, Swagman, and Wagenmakers (2017). The stopping rule required data collection from a minimum of 20 usable participants. (Participants' data were not considered usable if their session-wise accuracy was less than 90%; see the later section *Data Preparation* for full detail about the data trimming and exclusion criteria.) At this stage, Bayesian model comparison via Bayes factors was conducted¹. The data being modelled was the n-2 task repetition cost (calculated from log-transformed data; see the later section *Main Analysis Plan* for rationale) as the dependent variable, with the independent variables response-cue interval and n-2 response repetition².

¹Due to the scheduling of the first batch of data collection, the first peek at the data did not occur until 30 subjects had been recruited.

²Note that the full design is a three-factor design with the factors Task Sequence, RCI, and Response Repetition. However, for the stopping rule I used the two-factor design with the n-2 repetition cost as the DV and RCI and Response Repetition as independent variables as this reduces the number of models that are compared when using Bayes factors for factorial designs. The approach used for the stopping rule allows the critical question of the research to be focussed upon: whether the n-2 repetition costs for n-2 response

This analysis proceeds via a model comparison process. Each model entering the comparison differs from the others in terms of its inclusion of main effects of factors and their possible interaction. All models included “Participant” as a random effect. Four models were compared: 1) A model with just a main effect of RCI; 2) A model with just a main effect of Response Repetition; 3) A model with main effects of RCI and Response Repetition; and 4) a model with the main effects of RCI and Response Repetition, plus their interaction (hereafter the “full model”). For each model, a Bayes factor (BF) was calculated, which provides a ratio of the model’s evidence—given the current data—against a “null” model consisting of just the random effect.

As the full model is the critical test of the research question, the stopping rule depended on the ratio of the full model’s Bayes factor in comparison to the next-best model’s Bayes factor (or the best overall model if the full model is not the best). This comparison produces a new Bayes factor showing the degree of support for one model compared to the other. Thus, the critical Bayes factor, $BF_{Critical}$, indicating the support of the full interaction model is given by

$$BF_{Critical} = \frac{BF_{Full\ Model}}{BF_{(Next)\ Best\ Model}}$$

This critical Bayes factor was assessed after every participant; the stopping rule was that data collection would continue until the Bayes factor for this comparison went over 6 (indicating support for the full model) or under 1/6 (indicating support against the full model). If the $BF_{Critical}$ had not reached either criterion by 75 participants, data collection would cease.

The final sample consisted of 75 participants. Four additional participants were removed from the final analysis: One due to experimenter error; one due to inattentiveness throughout the study (the participant was closing their eyes for prolonged periods); and two due to session-wise accuracy below 90%. Although an arbitrary criterion, I have used this

repetitions and n-2 response switches are differentially affected by the RCI manipulation.

criterion in previous studies (see for example Grange et al. (2017)).

Apparatus & Stimuli

Stimuli were presented on a 17in. monitor connected to a PC running PsychoPy (Pierce, 2007). The code for the program can be downloaded from <http://bit.ly/2uwnOCg>. Responses were collected via a 1ms-precise USB keyboard. The stimulus display consisted of a black square frame (width/height of 250 pixels) on a grey background. The target was a black circle measuring 25 pixels in radius. Possible cues were the shapes square, triangle, and hexagon; all had a radius of 50 pixels.

Procedure

The task required participants to mentally make a spatial transformation of the target's location according to the currently-relevant rule, and to make a spatially-congruent response to the transformed location. Participants knew which rule is relevant by way of a task cue.

Each trial began with the presentation of a blank square frame for a variable period, depending on the current RCI condition: 50ms in the “short” condition, and 1,000ms in the “long” condition. After this time, a cue appeared in the centre of the frame for 150ms, after which the target circle appeared in one of the four corners. The target position was 127 pixels diagonally from the centre of the frame. Target location was chosen randomly on each trial. The cue and target remained visible until a response was recorded from the participant.

Each of the three cues were paired with one spatial transformation rule; for example, the square might cue a “diagonal” transformation, the triangle might cue a “horizontal” transformation, and the hexagon might cue a “vertical” transformation (see Figure 1). The cue–rule pairings were fully counterbalanced across participants. Responses were made on the numerical component of the response keyboard, using the keys “1”, “2”, “4”, and “5” to indicate an lower-left, lower-right, upper-left, and upper-right response, respectively . Participants were asked to respond as quickly and accurately as possible as soon as the target appeared, using their right index finger; instructions also asked participants to reset

their finger location to the centre of the four response keys after each response. Once a response was registered, the frame went blank and the next trial began. If an error was made, the word “Error!” appeared in red font in the centre of the screen for 1,000ms. The cue for the next trial was selected randomly with the constraint that no rule-repetition trials could occur; inclusion of task repetitions has been shown to reduce estimates of the $n-2$ task repetition cost (Philipp & Koch, 2006).

The experiment was separated into two halves, with a single RCI being used for each half. The order of RCI presentation was counterbalanced across participants. Each half of the experiment consisted of 4 blocks of 120 trials, with a self-paced rest after each block. Each half was preceded by an opportunity for participants to memorise the cue–rule pairings, and exposure to a practice mini-block of 32 trials. If participants made more than 6 errors (i.e., $\sim 20\%$) the practice was repeated once.

Design

The experiment manipulated three factors in a fully-related design: *Task Sequence* ($n-2$ task repetition) [ABA] vs. $n-2$ task switch [CBA]); *Response Repetition* ($n-2$ response repetition vs. $n-2$ response switch); and *RCI* (short [50ms] vs. long [1,000ms]). Response time in milliseconds (ms) and percentage error were recorded.

Analysis Strategy

This section provides an overview of the analysis plan. Various software packages were used; all experimental data were prepared, analysed, and plotted using R (Version 3.4.0; R Core Team, 2017) and the R-packages *afex* (Version 0.18.0; Singmann, Bolker, Westfall, & Aust, 2017), *BayesFactor* (Version 0.9.12.2; R. D. Morey & Rouder, 2015), *dplyr* (Version 0.7.5; Wickham & Francois, 2016), *ggplot2* (Version 2.2.1; Wickham, 2009), and *papaja* (Version 0.1.0.9709; Aust & Barth, 2017).

Data Preparation

For the RT and error-rate analysis, the first two trials from each block were removed as they cannot be classified as ABA or CBA sequences. For the RT analysis, error trials and the two trials following an error were removed. For error analysis, just the two trials following an error were removed. RTs were trimmed by removing RTs shorter than 150ms and longer than 2.5 standard deviations above the mean for each participant for each cell of the experiment design.

Main Analysis Plan

Response time data and error data were analysed separately. The analysis for each DV proceeded in three sections. In the first section, standard null-hypothesis significance testing is presented³. Secondly, a Bayesian ANOVA (J. N. Rouder et al., 2017) was conducted with the $n-2$ task repetition cost as the dependent variable, and Response Repetition and RCI as the independent variables. The use of the $n-2$ task repetition cost as the DV removes one factor (Task Sequence) from the analysis; this is advantageous because the number of models considered in a Bayesian analysis of factorial designs increases exponentially with the number of factors (see J. N. Rouder et al., 2017 for discussion). In a final section, Bayesian parameter estimation of the effect of RCI on the $n-2$ task repetition cost for $n-2$ response repetitions and response switches is presented.

Note that response times were log-transformed prior to data analysis. As the primary measure of interest (the $n-2$ task repetition cost) is a difference score, one can expect larger costs in a condition with overall longer response times without differences in the latent psychological processes giving rise to the observed effects (Wagenmakers, Kryptos, Criss, & Iverson, 2012). It is a consistent finding that RTs in short-RCI conditions are longer than in

³The primary focus will be on the Bayesian analysis that follows. However, as psychology is arguably transitioning between NHST and Bayesian analysis, I report NHST too so that readers less familiar/comfortable (or in complete disagreement) with Bayesian analysis can still engage with the analysis.

long-RCI conditions, so we could expect larger n-2 task repetition costs in the short-RCI condition even if the latent psychological process leading to this cost is unaffected by RCI manipulations. Log transformation of data to some extent mitigates this issue by placing RTs from different conditions on a similar scale.

Overview of null hypothesis significance testing. This analysis consists of a three-way repeated measures analysis of variance with the factors *Task Sequence* (ABA vs. CBA), *Response Repetition* (n-2 response repetition vs. n-2 response switch), and *RCI* (short vs. long). The criterion for significance was set to $\alpha = .05$. The effect size reported is generalised eta squared (η_g^2), the recommended effect size for repeated measures designs (Bakeman, 2005).

Of critical interest is the presence/absence of a 3-way interaction; presence of such an interaction would provide evidence that the effect of RCI on the n-2 task repetition cost is different for n-2 response repetitions and n-2 response switches.

Overview of Bayes factor analysis. As stated when presenting the stopping rule, Bayes factors (BFs) were calculated for four models, each constructed to predict the n-2 task repetition cost (i.e., the data in Figure 2): 1) A model with just a main effect of RCI; 2) A model with just a main effect of Response Repetition; 3) A model with main effects of RCI and Response Repetition; and 4) a model with the main effects of RCI and Response Repetition, plus their interaction (the “full model”). Higher BFs indicates more support for the model. The default prior settings of J. N. Rouder et al. (2017) was used.

The main component of this analysis is a model comparison process: The ratio of the BF for the full model against the next-best model’s BF (or the best overall model if the full model is not the best) was calculated. This produces a new BF ($BF_{Critical}$) assessing the evidence in support (or against) the full model. Values of $BF_{Critical}$ above one indicate support for the full model; values of $BF_{Critical}$ below one indicate support against the full model.

Overview of Bayesian estimation of the effect of RCI. Bayes factors are suitable for hypothesis testing, but are not suitable to estimate the magnitude of a particular effect. Of interest to this analysis was an estimation of the change in the n-2 task repetition cost with increasing RCI for both n-2 response repetitions and switches. Therefore, calculation of BFs were supplemented by Bayesian estimation of the effect of RCI on the n-2 task repetition cost for n-2 response repetitions and switches.

This was achieved by calculating a difference score representing the change in n-2 task repetition cost from short RCIs to long RCIs; this is done separately for n-2 response repetitions and n-2 response switches. Then, separate Bayesian one-sample t-tests are conducted on each difference score (one for n-2 response repetitions and one for n-2 response switches) using the **BayesFactor** package of Morey and Rouder (2015); a default prior on the effect size d was used, distributed as a Cauchy distribution with scale parameter $r = 0.707$. One can then sample from the posterior distribution of the Bayesian t-test; the analysis collected 100,000 samples from the posterior distributions. These were then be presented as density functions (basically smoothed histograms), together with 95% highest-density intervals (HDIs); the 95% HDIs span the range of parameter values with greatest credibility, given the data and the prior distribution. This analysis thus provides estimation of plausible parameter values for the effect of the RCI on n-2 task repetition costs for n-2 response repetitions and response switches.

Results

Response Times

Mean response times for all factors of the design can be seen in Figure 3.

NHST. Mean response times were submitted to a 3-factor fully-related analysis of variance with the factors *Task Sequence*, *RCI*, and *Response Repetition*. There was a main effect of Task Sequence, with RTs slower to n-2 task repetitions ($M = 6.80$, $SE = 0.05$) than to n-2 task switches ($M = 6.74$, $SE = 0.05$), $F(1, 74) = 41.19$, $MSE = 0.00$, $p < .001$,

$\hat{\eta}_G^2 = .005$. There was also a main effect of RCI, with slower RTs to the short RCI ($M = 6.83$, $SE = 0.05$) compared to the long RCI ($M = 6.71$, $SE = 0.05$), $F(1, 74) = 27.89$, $MSE = 0.08$, $p < .001$, $\hat{\eta}_G^2 = .053$. There was a main effect of Response Repetition, with slower RTs to n-2 response switches ($M = 6.77$, $SE = 0.05$) than to n-2 response repetitions ($M = 6.75$, $SE = 0.05$), $F(1, 74) = 20.38$, $MSE = 0.00$, $p < .001$, $\hat{\eta}_G^2 = .002$.

There was a significant interaction of Task Sequence and RCI [$F(1, 74) = 32.39$, $MSE = 0.00$, $p < .001$, $\hat{\eta}_G^2 = .002$]; the n-2 task repetition cost was 0.08 for the short RCI [$t(74) = 8.18$, $p < .001$] and 0.03 for the long RCI [$t(74) = 1.97$, $p = .053$]. There was also a significant interaction of Task Sequence and Response Repetition [$F(1, 74) = 37.57$, $MSE = 0.00$, $p < .001$, $\hat{\eta}_G^2 = .004$]; the n-2 task repetition cost was 0.07 for n-2 response switches [$t(74) = 12.24$, $p < .001$], and 0.01 for n-2 response repetitions [$t(74) = 0.54$, $p = .587$].

The three-way interaction was not statistically significant, $F(1, 74) = 1.28$, $MSE = 0.00$, $p = .262$, $\hat{\eta}_G^2 = .000$. The reduction of the n-2 task repetition cost with increasing RCI was similar for n-2 response switches and for n-2 response repetitions, which is best visualised in Figure 4 which plots the n-2 task repetition cost as the dependent variable.

Bayes factors. The data in Figure 4 was modelled using the methods for Bayesian analysis of factorial designs as outlined by J. N. Rouder et al. (2017). This analysis proceeds via model comparison, where the models differ in terms of their inclusion of main effects of factors and their interaction. All models included “Participant” as a random effect, and were predicting the n-2 task repetition cost as the dependent variable.

The Bayes factor for the full model (main effects of RCI and Response, plus their interaction) was $BF = 1,499,526,744,685.78$. The model with the highest BF was the model including just main effects of RCI and Response ($BF = 5,045,318,516,284.97$). Thus, the critical Bayes factor was $BF_{Critical} = 0.30$. This suggests that the data are ~3 times more likely under the two-main effects model compared to the full interaction model. This

provides moderate evidence against the full interaction model and in support of the two main effects model.

This analysis compliments the NHST analysis in that whilst the n-2 task repetition cost decreases with RCI and is overall larger for response switches, the reduction of the n-2 task repetition cost with increasing RCI is not different for response repetitions and response switches.

Bayesian estimation. The Bayesian estimation of the magnitude of the reduction of n-2 task repetition cost with increasing RCI is shown in Figure 5. There appears some overlap between the posterior distribution for response repetitions and response switches, although there is a trend for the RCI effect for response switches to be larger than for response repetitions. For n-2 response switches, the mean reduction in n-2 task repetition cost from short to long RCIs was 0.05, 95% HDI [0.04, 0.07]. For n-2 response repetitions, the mean reduction in n-2 task repetition cost from short to long RCIs was 0.03, 95% HDI [0.01, 0.06].

Error Rates

Mean error rates for all factors of the design can be seen in Figure 6.

NHST. Mean error rates were submitted to a 3-factor fully-related analysis of variance with the factors *Task Sequence*, *RCI*, and *Response Repetition*. There was no significant main effect of Task Sequence, with similar error rates to n-2 task repetitions ($M = 2.73$, $SE = 0.28$) and n-2 task switches ($M = 2.71$, $SE = 0.34$), $F(1, 74) = 0.01$, $MSE = 4.21$, $p = .936$, $\hat{\eta}_G^2 = .000$. There was a significant main effect of RCI, with higher error rates to the short RCI condition ($M = 3.05$, $SE = 0.33$) compared to the long RCI condition ($M = 2.39$, $SE = 0.29$), $F(1, 74) = 12.21$, $MSE = 5.34$, $p = .001$, $\hat{\eta}_G^2 = .015$. There was also a main effect of Response Repetition, with higher error rates to n-2 response switches ($M = 2.98$, $SE = 0.30$) than to n-2 task repetitions ($M = 2.45$, $SE = 0.33$), $F(1, 74) = 11.57$, $MSE = 3.68$, $p = .001$, $\hat{\eta}_G^2 = .010$.

There was no significant interaction of Task Sequence and RCI [$F(1, 74) = 0.97$, $MSE = 4.81$, $p = .328$, $\hat{\eta}_G^2 = .001$]. However, there was a significant interaction of Task Sequence and Response Repetition [$F(1, 74) = 35.81$, $MSE = 2.83$, $p < .001$, $\hat{\eta}_G^2 = .023$]; the n-2 task repetition cost was 0.84% for n-2 response switches [$t(74) = 5.41$, $p < .001$], and was a facilitatory effect of -0.81% for n-2 response repetitions [$t(74) = -3.06$, $p = .003$].

The three-way interaction was not statistically significant, $F(1, 74) = 0.37$, $MSE = 3.60$, $p = .543$, $\hat{\eta}_G^2 = .000$. The reduction of the n-2 task repetition cost with increasing RCI was similar for n-2 response switches and for n-2 response repetitions, which is best visualised in Figure 7 which plots the n-2 task repetition cost as the dependent variable.

Bayes factors. The data in Figure 7 was modelled in the same way as for response times.

The Bayes factor for the full model (main effects of RCI and Response, plus their interaction) was $BF = 3,909.38$. The model with the highest overall BF was the model including just the main effect of Response ($BF = 80,271.40$). Thus, the critical Bayes factor was $BF_{Critical} = 0.05$. This suggests that the data are ~ 20.53 times more likely under the single-main effect of Response model compared to the full interaction model. This provides strong evidence against the full interaction model, in favour of the model where just Response influences the n-2 task repetition cost.

Bayesian estimation. The Bayesian estimation of the magnitude of the reduction of n-2 task repetition cost with increasing RCI is shown in Figure 8. As with the RT analysis, there appears some overlap between the posterior distribution for response repetitions and response switches, although there is a trend for the RCI effect for response switches to be larger than for response repetitions. For n-2 response switches, the mean reduction in n-2 task repetition cost from short to long RCIs was 0.52%, 95% HDI [-0.07%, 1.10%]. For n-2 response repetitions, the mean reduction in n-2 task repetition cost from short to long RCIs was 0.16%, 95% HDI [-1.00%, 1.32%].

General Discussion

The purpose of the present study was to re-examine the effect of residual task activation (as manipulated via the RCI) on the $n-2$ task repetition cost, a measure thought to reflect inhibition. Importantly, though, the current study controlled for episodic retrieval effects to examine whether RCI manipulations influenced inhibition or episodic retrieval.

The data showed strong effects of episodic retrieval on the $n-2$ task repetition cost, replicating our earlier work (Grange et al., 2017). Specifically, the $n-2$ task repetition cost was absent for $n-2$ response repetitions (i.e., episodic matches) in the response time data, and turned into an $n-2$ task repetition *benefit* for accuracy data. In contrast, there were large $n-2$ task repetition costs for $n-2$ response switches (i.e., episodic mismatches) in both the response time and accuracy data. These data support the conclusion of Grange et al. (2017) that much of the $n-2$ task repetition cost is caused by interference during episodic retrieval, rather than purely inhibition, at least in the current paradigm.

Increasing the RCI led to smaller $n-2$ task repetition costs in the response time data, replicating earlier work (Gade & Koch, 2005; Grange & Houghton, 2009; Mayr & Keele, 2000). Importantly for the current work, though, this reduction in $n-2$ task repetition cost was similar for $n-2$ response repetitions and $n-2$ response switches, corroborated by both the frequentist analysis (i.e., a lack of a three-way interaction in RT and accuracy data) and the Bayesian analysis (the preference of the Bayes factors for a 2-main-effects model, as well as the Bayesian estimation of the magnitude of the reduction of the $n-2$ task repetition cost with increasing RCI). Thus, relating back to the hypothetical outcomes outlined in the introduction, the current data are most consistent with Figure 2B, which suggests RCI has an equal effect on episodic interference components of the $n-2$ task repetition cost (i.e., $n-2$ response switches) and inhibition components of the $n-2$ task repetition cost (i.e., $n-2$ response repetitions).

However, it is important to note that whilst the reduction of the cost with increasing RCI is consistent for $n-2$ response repetitions and $n-2$ response switches, the overall

magnitude of the cost is very different. For $n-2$ response repetitions in the response time data, an increasing RCI reduces the $n-2$ task repetition cost from a modest cost to no cost at all (see solid lines in Figure 4); for $n-2$ response switches, although the cost reduces with increasing RCI, there is still a cost present at long RCIs (see dashed lines in Figure 4). The same pattern is largely true also for the error data, except there is $n-2$ task repetition facilitation for both short and long RCIs for $n-2$ response repetitions (episodic matches).

These findings have important theoretical implications, given the proposed tight link between task activation, task interference, and subsequent deployment of task inhibition (e.g., Gade & Koch, 2005; Sexton & Cooper, 2017). For instance, in the computational model of Sexton and Cooper (2017), response nodes are biased toward the correct response via top-down input from task demand units (one for each task), which themselves are activated via the relevant task cue. The activation of task demand units carry-over from one trial to the next; on task switches, the currently-relevant task demand unit becomes activated from the task cue, but the recently-performed task’s demand unit retains some activity, leading to interference. In the model, the system is sensitive to the level of interference, and deploys inhibition proportionally. Importantly, the activation of task demand units decay passively as a function of time when receiving no input from task cues. Therefore, if more time has passed since task performance (i.e., at long RCIs), activation of a new task demand unit will meet with less interference, and hence less inhibition is deployed. Thus, the model predicts well the reduction of the $n-2$ task repetition cost with increasing RCI. However, given that now sufficient evidence has been reported that a considerable portion of the $n-2$ task repetition cost is driven by episodic interference, it would be important to extend the model of Sexton and Cooper (2017) to incorporate episodic retrieval effects. This work would assist in understanding the processes underlying the rather complex trade-off seen in the response time and accuracy data: For $n-2$ response repetitions there is an $n-2$ task repetition *cost* for the RTs (albeit small), but an $n-2$ task repetition *benefit* in the accuracy.

One possible extension is to utilise the Parallel Episodic Processing (PEP) model of

Schmidt, DeHouwer, and Rothermund (2016). The PEP model is a connectionist model designed to simulate behaviour (i.e., response times and accuracy) in cognitive paradigms (e.g., the Stroop task). Importantly in this model, episodic traces are stored on every trial, which bind together the stimulus that was presented on the current trial as well as the response that was executed. When this stimulus is encountered again, all episodic traces related to this stimulus are retrieved and can influence response performance on the current trial.

The Sexton and Cooper (2017) model could be extended to incorporate this aspect of the PEP model (Schmidt et al., 2016) by allowing an episodic trace to be stored on every trial which captures the activation pattern across the input layer (i.e., the stimulus presented), the task demand layer (i.e., which task is being cued) and the response layer (i.e., which response is activated). Upon presentation of a particular task in the future, the episodic traces associated with this task can be retrieved and allowed to influence response selection. Such a model will begin to address the extent to which inhibition and episodic retrieval jointly contribute to the $n-2$ task repetition cost in task switching.

The current work, and that of Grange et al. (2017), sits within a broader context of work demonstrating a role of episodic memory retrieval in explaining (or at least, contributing to) key effects in the task switching literature. For example, work has shown a considerable contribution of episodic (and semantic) memory retrieval to the task switch cost—the observed slowing of RTs on task switch trials compared to task repetition trials—in the explicitly-cued task switching paradigm (Altmann & Gray, 2008; Logan, 2003; Schmidt & Liefoghe, 2016; Schneider & Logan, 2005). The observed reduction of the task switch cost with increasing RCI—once attributed to the time-based decay of task-set activation (Meiran, Chorev, & Sapir, 2000)—has been shown to be attributable to temporal distinctiveness effects during automatic, cue-based retrieval of task-sets from episodic memory (Grange, 2016; Grange & Cross, 2015; Horoufchin et al., 2011). More recent work has shown that the congruency effect in task switching—slowed responding to incongruent

stimuli which afford more than one response (depending on task) compared to congruent stimuli which afford just one response irrespective of task—can be explained by memory retrieval processes (Schneider, 2014, 2015; Schneider & Logan, 2015). The current work—and that of Grange et al. (2017)—contributes to this body of work by showing that the $n-2$ task repetition cost to a large extent can also be explained by episodic memory retrieval.

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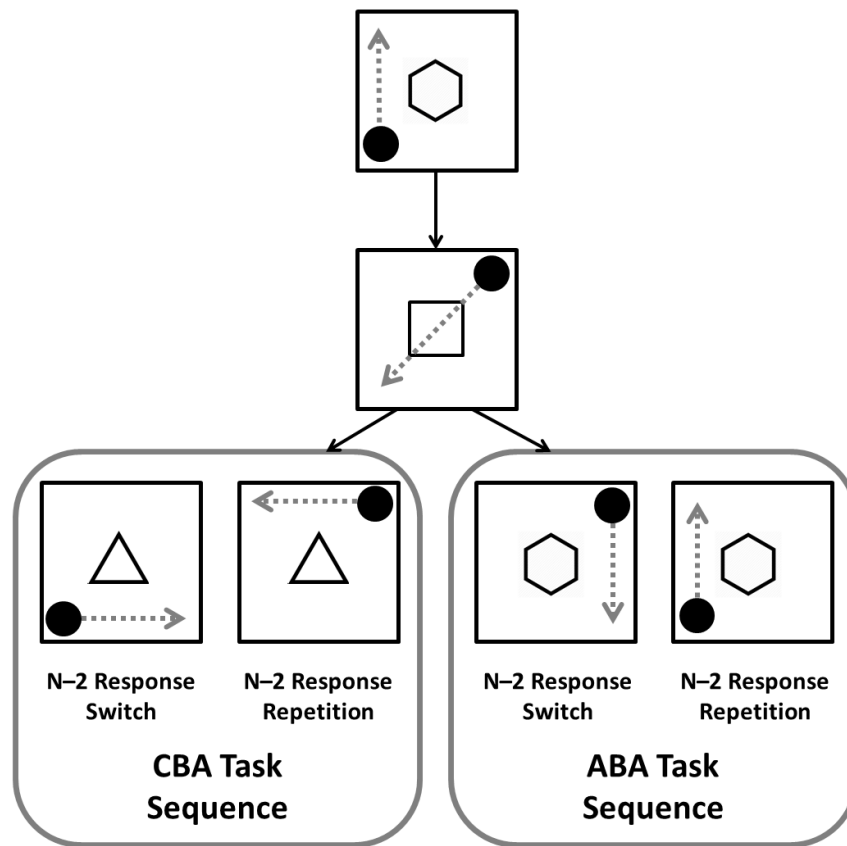


Figure 1. Schematic of the experimental paradigm. The arrows represent the spatial transformation required on each trial; these were not shown to participants. Time runs from the top to bottom of figure. Note that the image is not drawn to scale. Figure available at <https://www.flickr.com/photos/150716232@N04/shares/5413G0> under CC licence <https://creativecommons.org/licenses/by/2.0/>

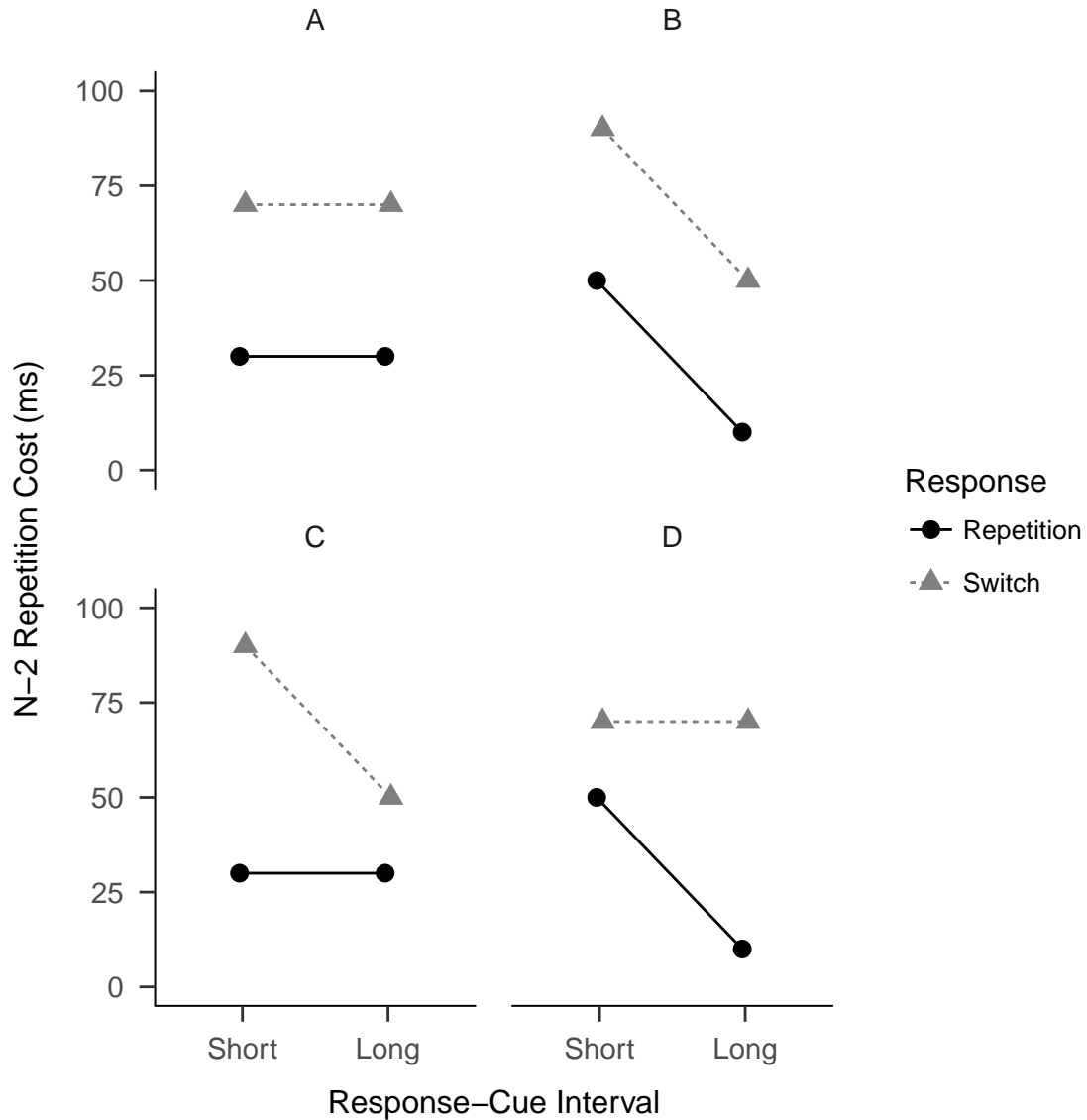


Figure 2. Different predictions for the n-2 repetition cost (in milliseconds, ms) as a function of the independent variables n-2 Response Repetition (repetition vs. switch) and Response-Cue Interval (RCI; short vs. long). Note that the scale is arbitrary. **A.** Main effect of Response. **B.** Main effect of Response and RCI. **C.** Interaction between Response and RCI. Here, RCI affects response switches selectively. **D.** Interaction between Response and RCI. Here, RCI affects response repetitions selectively.

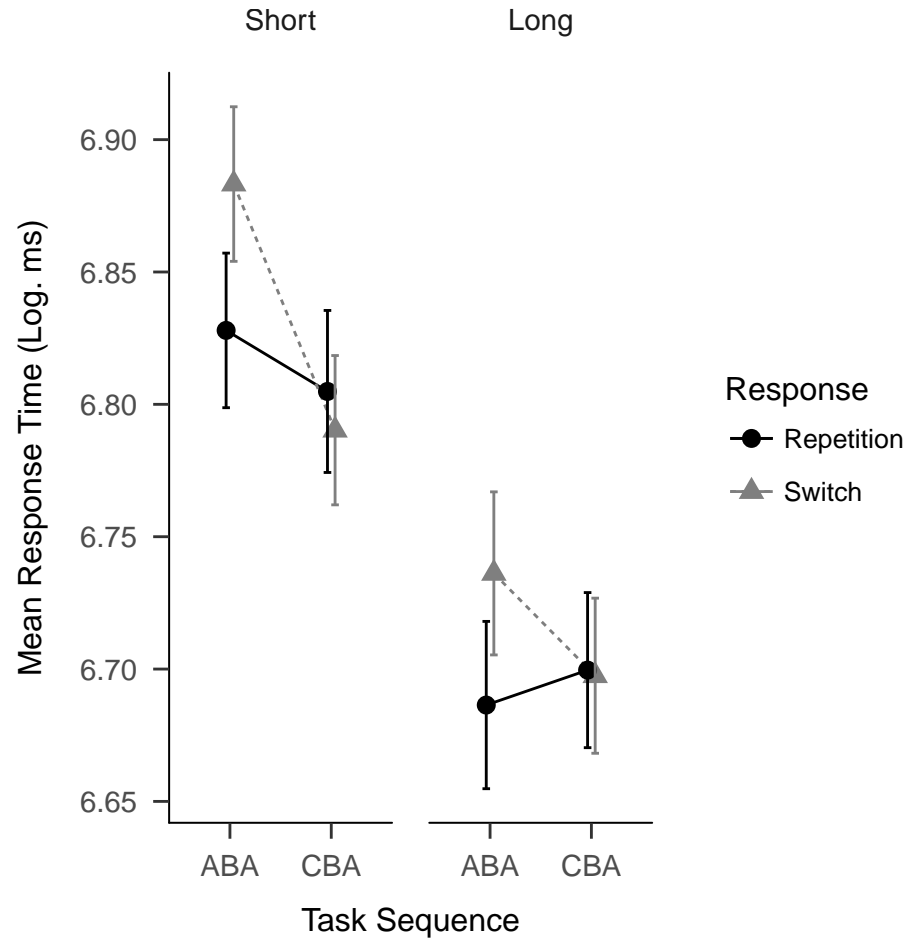


Figure 3. Mean log transformed response times (in milliseconds, ms) for ABA and CBA sequences as a function of response-cue interval (Short vs. Long) and response repetition (repetition vs. switch). Error bars denote ± 1 standard error around the mean.

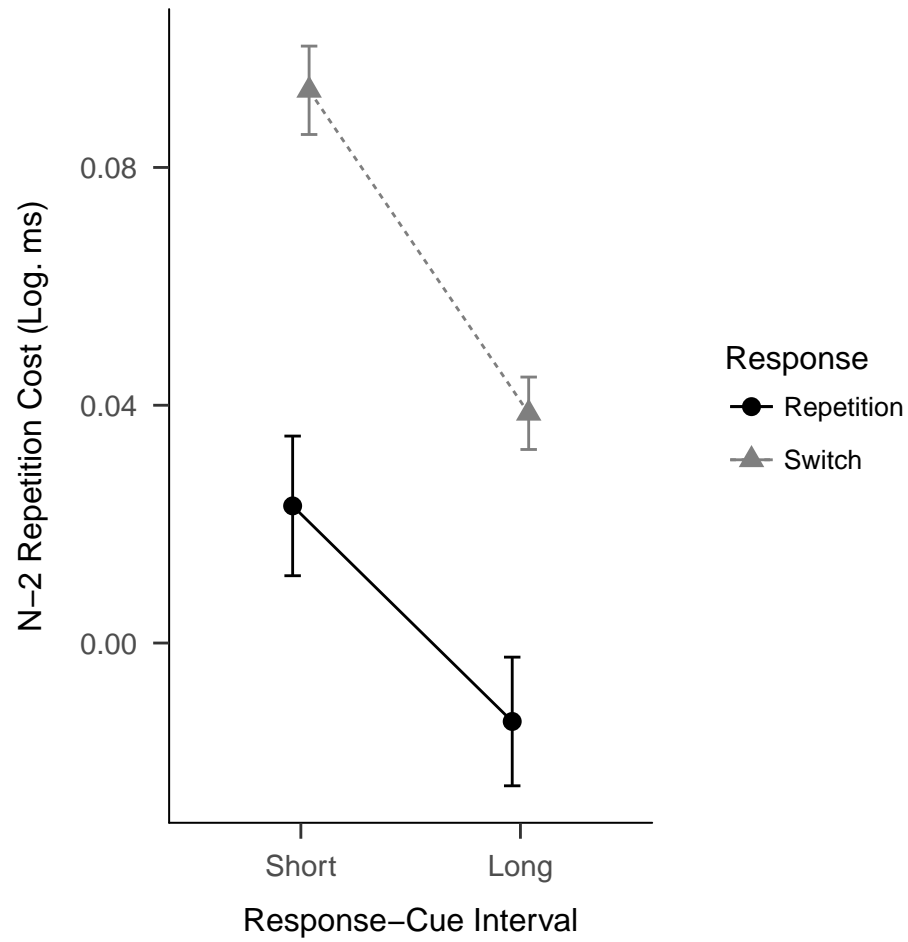


Figure 4. Mean n-2 task repetition cost (log-milliseconds) as a function of response-cue interval and response repetition. Error bars denote +/- 1 standard error around the mean.

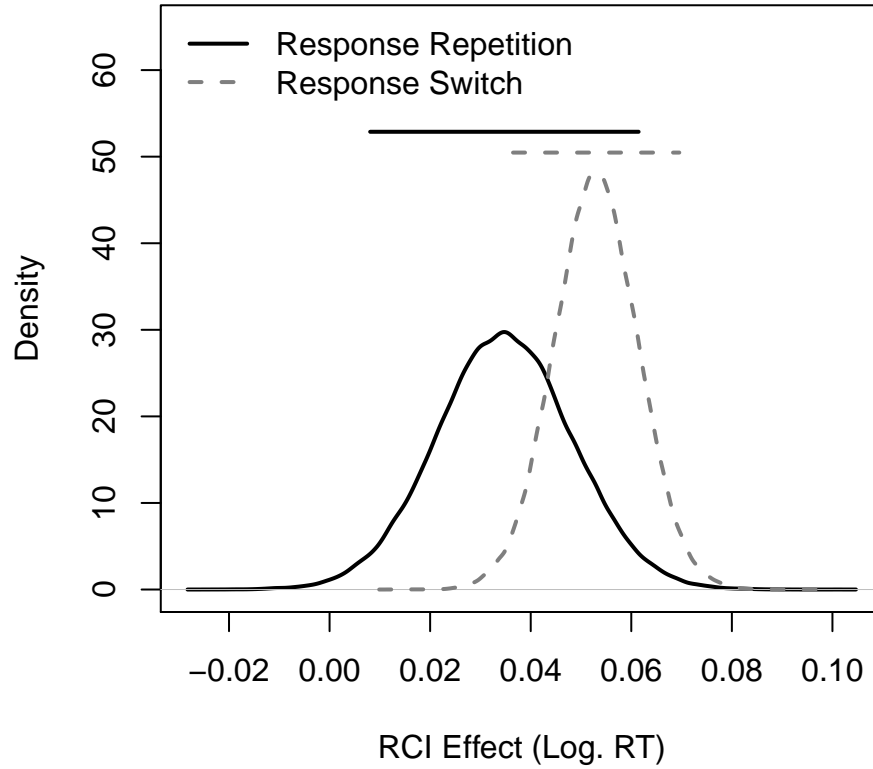


Figure 5. Density functions of the Bayesian posterior distributions of the response-cue interval (RCI) effect on the $n-2$ task repetition cost in log RT for $n-2$ response repetitions and $n-2$ response switches. The RCI effect is defined as the difference in $n-2$ task repetition cost for short and long RCIs. The horizontal bars denote the 95% highest density intervals for each density function.

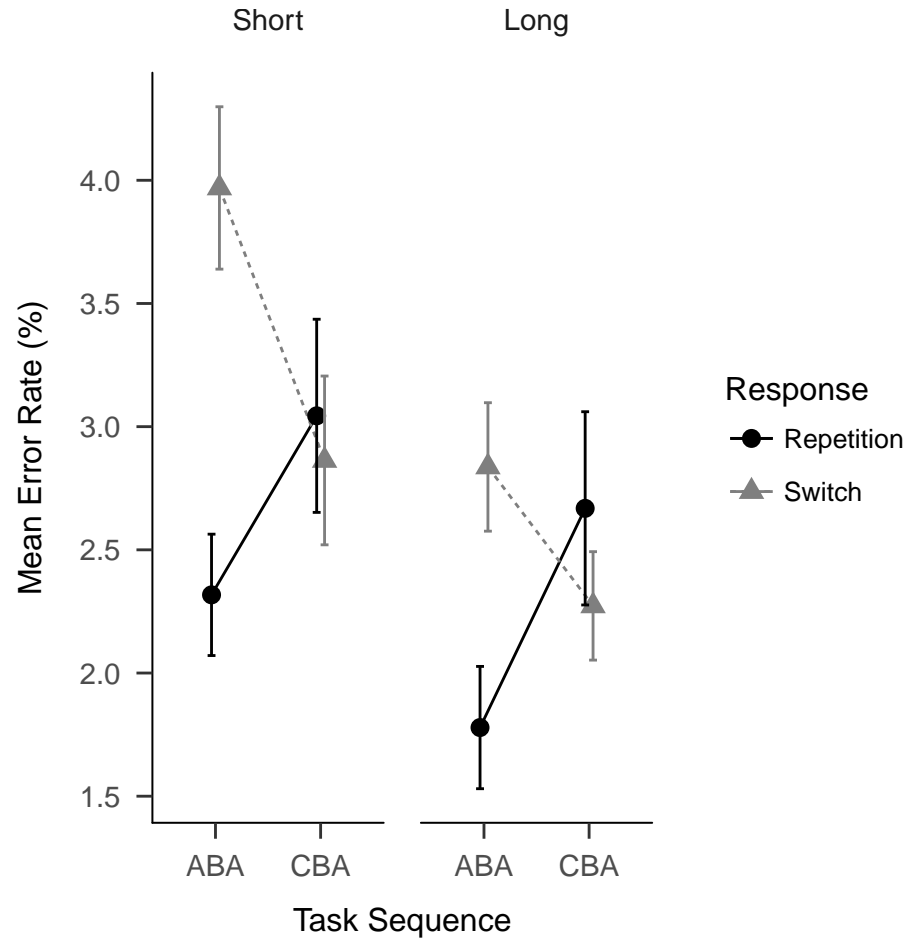


Figure 6. Mean error rates (in percentage) for ABA and CBA sequences as a function of response-cue interval (Short vs. Long) and response repetition (repetition vs. switch). Error bars denote ± 1 standard error around the mean.

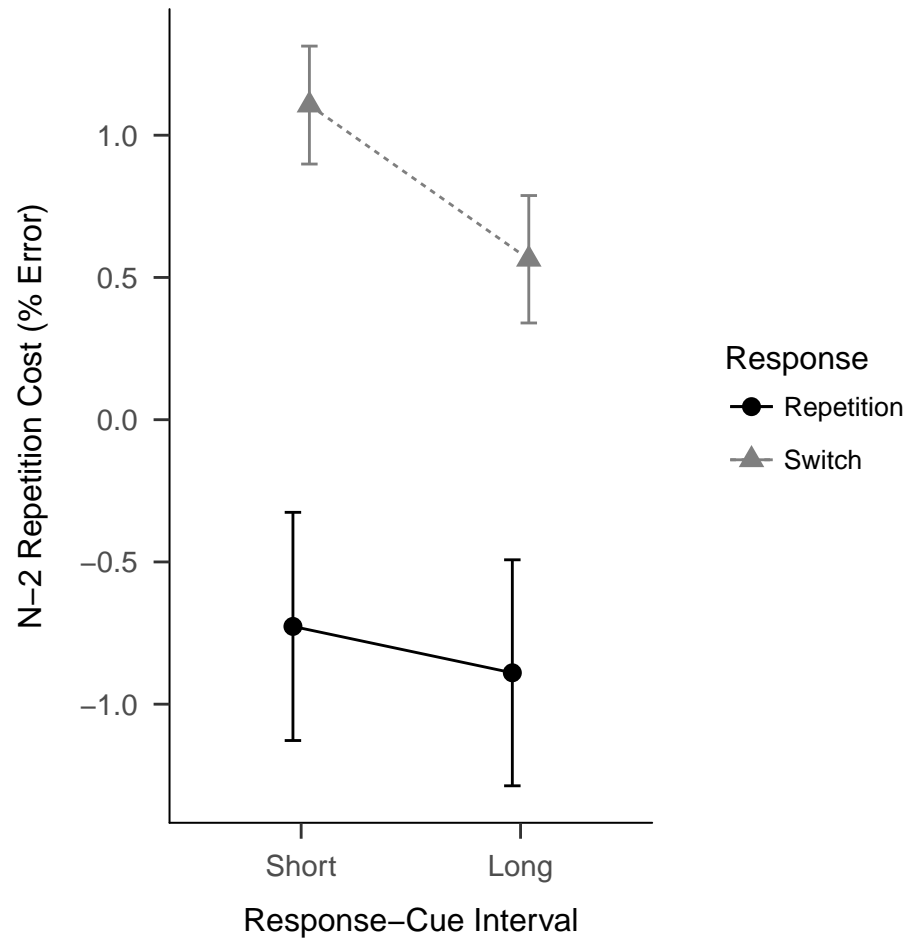


Figure 7. Mean n-2 task repetition cost (percent Error) as a function of response-cue interval and response repetition. Error bars denote ± 1 standard error around the mean.

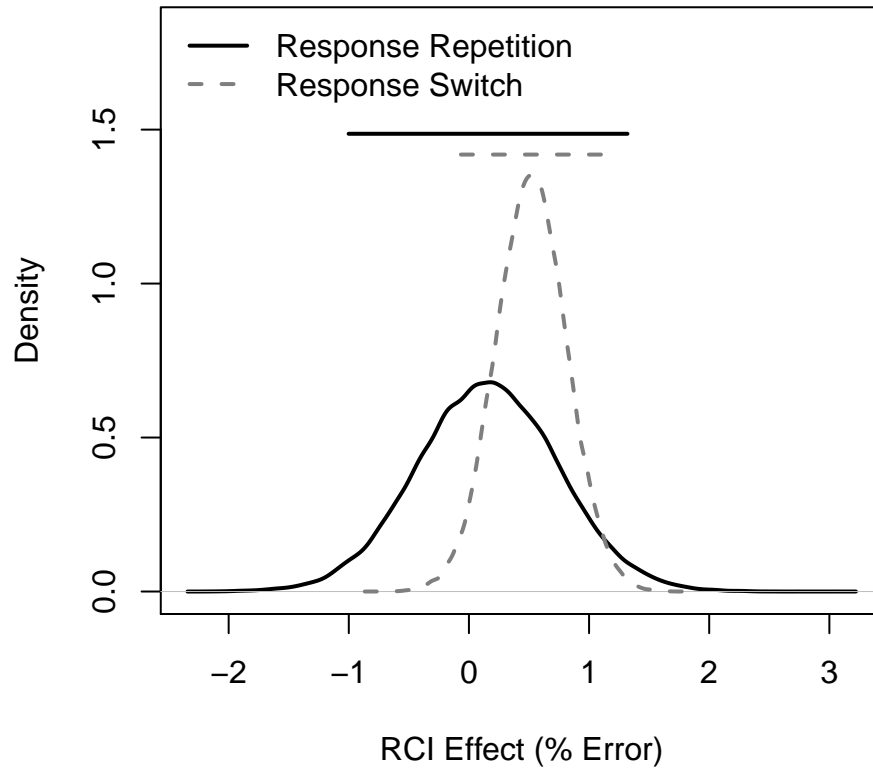


Figure 8. Density functions of the Bayesian posterior distributions of the response-cue interval (RCI) effect the $n-2$ task repetition cost in percentage error for $n-2$ response repetitions and $n-2$ response switches. The RCI effect is defined as the difference in $n-2$ task repetition cost for short and long RCIs. The horizontal bars denote the 95% highest density intervals for each density function.